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Foreground Extraction Using Hilbert-Schmidt Independence Criterion and Particle Swarm Optimization Independent Component Analysis

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ABSTRACT

Foreground extraction is one of the crucial subjects in image processing, which drives different applications in industry. The reality behind the continuous research in this area is the various challenging problems we encounter during the separation process of foreground and background images. Among the source separation approaches, the independent component analysis (ICA) is the most prevalent, being involved in different areas of signal separation applications. Despite the improvements being achieved in foreground extraction, the sudden luminance variations and background movements adversely impact the results of techniques in this regard. In this paper, a novel structure called HSIC_ICA is introduced to address the mentioned problem using a modified version of the ICA algorithm which, leverages the Hilbert-Schmidt Independence Criterion (HSIC) instead of the common objective functions. Moreover, the unmixing matrix elements of ICA are extracted through a Particle Swarm Optimization (PSO) evolutionary algorithm in a much faster way. The experimental results clearly show that the proposed method outperforms over the significant works being cited among the references, using Wallflower dataset.

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1. INTRODUCTION

Foreground extraction or Background subtraction is a widely used real-time method for identifying foreground objects in a video stream which drives many applications in industry, including: video surveillance [1], human-machine interaction [2], content based video coding [3] and so on. This is active research due to the problems we encounter during the separation process.

There are four requirements for the background subtraction: (1) extraction must be performed in real time, (2) memory consumption must be limited, (3) the image must be extracted with little noise, and (4) the boundaries of the objects must be clear [4].

The goal of the foreground extraction is to separate the foreground object from a reference background image. There are significant challenges in the foreground extraction task, which directly affects the outcome of existing methods. The challenges are normally caused by the variations in illumination, shadows, camouflage, camera noise and light switching, to name a few.

There are several approaches being introduced to tackle the aforementioned problems.The simple solution was to subtract the given background image from the mixed background plus foreground one. However, this only works if there are no variations in the background, over the course of the process [5]. Statistical methods try to estimate the foreground image using a probabilistic framework [6]. Clustering methods elaborate to find clusters and assign the foreground-associated pixels to the most relevant cluster based on a reasonable objective function [7]. Neural networks methods are further learned by some training data to distinguish the foreground images and are highly affected if an unseen object suddenly moves into the background [8]. They are also data dependent and their accuracy is highly relevant to the number of the data samples as well as the compatibility of the training and testing conditions.

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Here, the pure background image may belong to a frame with a completely different illumination and shadowing conditions. Moreover, the camera is assumed to be fixed during the process.

In this paper, alongside the component analysis approaches [9–11], the concept of the Hilbert-Schmidt independence criterion (HSIC) is used as a measure of the distance in the cost function of the independent component analysis, which expedites the foreground extraction task compared with the antecedent methods. Despite, the previous kernel independence measures, HSIC has several advantages. First, the empirical estimate is much simpler (just the trace of a product of Gram matrices). Second, HSIC does not require extra regularisation terms for a good finite sample behaviour. Furthermore, independence tests based on HSIC do not suffer from slow learning rates. In particular, kernel methods are substantially more resistant to outliers than other specialised ICA algorithms [12–14].

The remainder of the paper is organized as follows: In section 2, we breifly review related works. Section 3 explains the basic model being used to tackle the problems. Section 4 introduces the proposed method along with mathematical explanations. The datasets, the experiments and the results together with brief analytics are presented in section 5. The conclusion wraps up the work.

2. RELATED WORKS

There are various approaches of background subtraction. In this research, we compare our method with significant methods published so far. The detection of moving objects from a video frame provides a classification of the pixels into either foreground or background. Most Background subtraction methods adopt the strategy of updating background model to overcome the aforementioned challenges. However, these kinds of methods are always computationally expensive.

Schindler and Wang [15] proposed an efficient way to account for spatial smoothness in foreground-background segmentation of video sequences. They optimized the output of the Mixture of Gaussian with a Markov Random Field in their smooth foreground-background segmentation and the results were impressive.

VIBE [16] is another significant background subtraction algorithm which has been developed by Barnich and Droogenbroeck. It uses a stochastic maintenance strategy to integrate new information into the model. If the pixel in the new frame matches some of the background samples, it is classified as background and has a probability of being inserted into the sample model at the corresponding pixel location.

Shimada and Taniguchi [17] proposed a hybrid type of background model that are robust to long-term and short-term illumination changes named "hybrid spatial-temporal background model".

Dou et al. [18] proposed a foreground detection method based on Convolutional Neural Networks to deal with challenges confronted with background subtraction. In this method, a background model is constructed using CNN's pre-trained model for each window which is made of a clean background image. Tsai and Lai [19] has applied ICA for background subtraction for indoor surveillance. They have combined ICA along with particle swarm optimisatin(PSO) in their approach. Another proposition based on contour and ICA based segmentation is proposed by Sekkati et al. [20].

3. BASIC APPROACH

The simplest form of ICA model is the linear mixing version, usually called Classical ICA model. In this Scenario, X is expressed as:

$$X=AS \tag{1}$$

where $X=[x_1,x_2,...,x_n]$ denotes the observed mixture signals, A denotes unknown mixing coeffient matrix and S is the latent source signals. The problem of ICA is to identify A and S from the knowledge X or in other words, to estimate A from observed X. To address this problem, Tsai and Lai combined ICA along with particle swarm optimization in their approach.

The proposed ICA process consists of two phases: the learning phase and the detection phase. During the learning phase, the ICA algorithm finds a matrix $W=A^{-1}$, which minimizes the absolute difference between the joint probability density function and the product of marginal probability density functions as follows:

$$G(WX)=\min\sum_{k=1}^{K}|P(y_{1k},y_{2k})-P_1(y_{1k})\times P_2(y_{2k})| \tag{2}$$

where, $K=1,2,...,k$; $i=1,2$ and y_{ik} is the estimated foreground or background signal. Then histograms obtained from the images are employed to estimate joint PDF ($P(y_{1k},y_{2k})$) and marginal PDFs ($P_1(y_{1k})$ and $P_2(y_{2k})$).

The second phase of the ICA algorithm is the actual source separation. Independent components can be computed by applying the unmixing matrix **W** to the initial data:

$$S=WX \tag{3}$$

In the training stage, the de-mixing matrix is achieved. Then, in the detecting stage, (3) is used to get the independent source signals $\mathbf{Y}=[y_1,y_2]$ which contain a foreground and background signal. The complete process is shown in Figures 1 and 2.

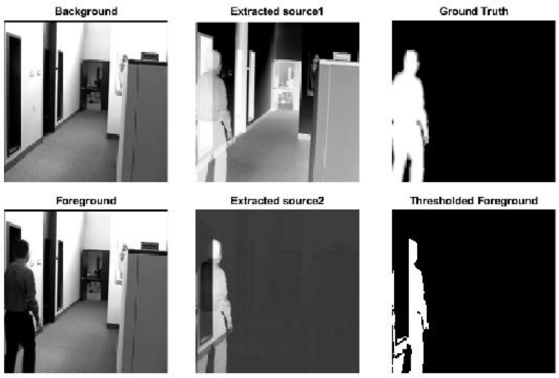

Figure 1. HSIC-ICA training phase

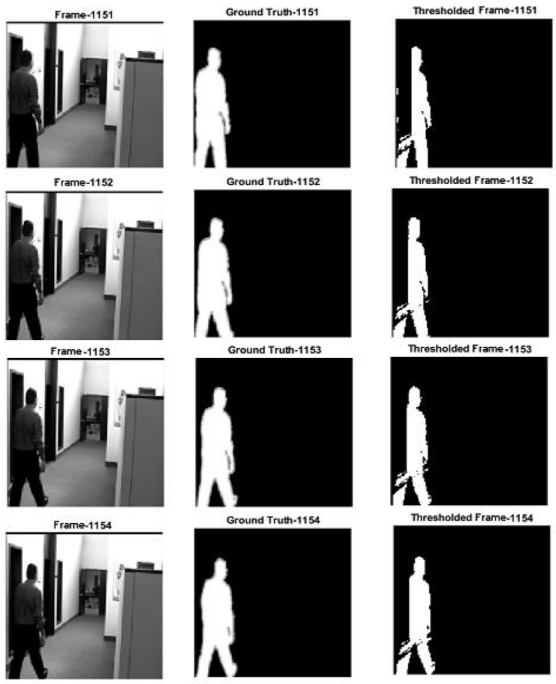

Figure 2. HSIC-ICA detection phase with W=[-0.864, -0.223; -0.002, 0.00237] and threshold of tr.=1.2

Let W=[w_{11},w_{12}; w_{21},w_{22}] denotes the unmixing matrix obtained from corresponding foreground and reference background image. To understand whether y_1 or y_2 is foreground, The following constraints must be satisfied:

$$\begin{cases} w_{11} \cdot w_{12} < 0, w_{21} \cdot w_{22} > 0 \\ w_{11} \cdot w_{12} < 0, w_{21} \cdot w_{22} < 0, w_{12}/w_{11} > w_{22}/w_{21} \\ w_{11} \cdot w_{12} > 0, w_{21} \cdot w_{22} > 0, w_{12}/w_{11} < w_{22}/w_{21} \end{cases} \quad (4)$$

4. PROPOSED METHOD

Inspired by [19], we introduce a new ICA model to avoid hole and part-missing in the foreground mask. Despite the improvements that have been achieved so far, limitations still remain. Namely, applying the definition of statistical independence in (2) is difficult, there is no prior knowledge of the joint and marginal PDFs. Contrary to the basic ICA, we propose using Hilbert-Schmidt Independence Criterion (HSIC) to achieve the independence of the outputs. The building block of the basic ICA is modified. The structure of the system being used to perform the foreground extraction task is depicted in Figure 3.

In this structure, the ICA with two inputs and two outputs are considered. The reference background, along with the current frame are fed to the ICA block. Assuming that the foreground and background images are two independent sources, ICA algorithm is employed to separate them. In addition, the PSO algorithm is employed as the optimization algorithm with which the cost function is minimized. Finally, we use morphological operators to remove holes and noisy parts of the foreground mask.

4. 1. HSIC Before expressing the idea of HSIC, it is necessary to express another idea, called maximum mean discrepancy(MMD) [21], proposed by the same HSIC researchers. This idea uses the kernel idea in Hilbert space [22], mapping the comparative data to the kernel space, and then obtaining a linear comparison in the kernel space, which in the original space is equivalent to comparing all the statistics of two random variables. Suppose we have two Gaussian random variables like X and Y, each of which follow a probability density function like p and q. If we want to calculate the similarity of these two variables, we cannot do this using the mean criterion, because the means are equal and so the difference will be zero. Now, if the variances are compared, the difference is clear, and it can be seen that there are differences between the two Gaussian random variables. We can generalize this idea to a higher dimensional space and show the following vector under the following mapping function like:

$$\chi \xrightarrow{\varphi} \begin{bmatrix} X \\ X^2 \end{bmatrix}, \quad \gamma \xrightarrow{\varphi} \begin{bmatrix} Y \\ Y^2 \end{bmatrix} \quad (5)$$

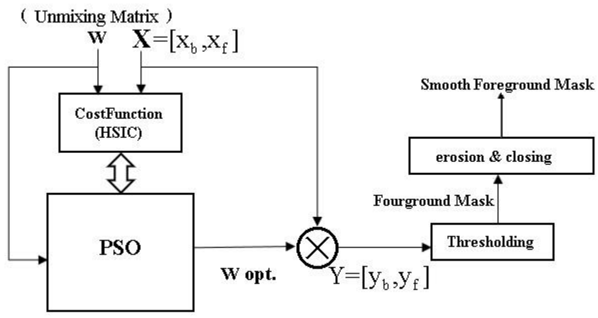

Figure 3. The proposed ICA structure

When our random variables are transformed from one-dimensional to two-dimensional, using the mean difference in the two-dimensional space we can find some kind of difference for both the mean and variance statistics in the one-dimensional space. Therefore, by computing the difference between the two means in two-dimensional space, the difference between the mean and the variances of the two variables in the one-dimensional space is calculated. This can be generalized to the difference between higher-order statistics if the transform or mapping function of these two one-dimensional random variables is mapped to the Hilbert space (which is an infinite-dimensional analytic space) in which dot product is a measure of similarity between two random variables, and according to the Mercer Theorem [23], in the kernel space a function can be found to represent a measure of similarity in the infinite dimensional space without having to map the one-dimensional variables first to this space, and Then we get this similarity in the kernel space. Thus, the difference between the two probability functions mentioned is:

$$|\text{p-q}|^2 = \left|\frac{1}{n}\sum_{\text{i}=1}^{n}\varphi(x_i) - \frac{1}{m}\sum_{\text{i}=1}^{m}\varphi(y_j)\right|^2 \quad (6)$$

Now this equation can be expanded as follows, which can be achieved by simplifying and applying the Mercer idea to the following:

$$|\text{p-q}|^2 = \frac{1}{n^2}\sum_{\text{i,j}}K(x_i,\text{x}_j) + \frac{1}{m^2}\sum_{\text{i,j}}K(y_i,\text{y}_j) - \frac{2}{\text{nm}}\sum_{\text{i,j}}K(x_i,\text{y}_j) \quad (7)$$

In the above relations, the function K() is the kernel function, which is replaced by the internal multiplication in the kernel space, and this function can be computed in the initial one-dimensional space. For example, the Radial Basis Function (RBF) kernel can be used for this purpose. This idea is called the Maximum Mean Discrepancy.

Now, if we want to examine the dependence between two random variables that have different probability functions, this idea can be used. Suppose we have random variables X and Y, each of which has the probability functions p, q. If these two random variables are independent, then the probability density function of these two should be multiplied by the sum of the probability functions of each. That is, in the following relation:

$$\text{HSIC\_Norm}=\|\mu(P_{\text{XY}})\text{-}\mu(P_X P_Y)\| \quad (8)$$

where μ represents the mean of the distribution function as the argument of this function. The P_{xy} and P_x, P_y further represent the joint pdf and the marginal pdfs belonging to the mixed signal and the individual background and foreground images, respectively. When this measure decays to zero, it implies that two distributions (P_{xy} and $P_x.\text{P}_y$) are equal, hence the X and Y signals are separated.

Now to calculate this criterion, we can use the same idea of the maximum mean discrepency. Thus, instead of computing independence in the original space, we compute the difference of the two covariance matrix differences between two random variables in the kernel space. Since the covariance (which is a linear operator) in the kernel space represents a measure of similarity in the kernel space, this covariance criterion in the original space will show the dependency between the two main random variables. This criterion has been shown in various forms in the kernel space, a well-known and standard criterion introduced by Hilbert and Schmidt is:

$$\text{HSIC(X,Y)} = \frac{1}{(\text{m-1})^2}\text{Trace(KHMH)} \quad (9)$$

where H is the centering matrix, which performs column centering and raw-centering when it is applied from left and right side of a matrix, respectively. M is the linear kernel which represents the covariance matrix over the estimated foreground signal. Further, K represents the radial-basis function kernel over the background image signal. Both kernels, are applied after vectorizing their corresponding input image signals. The ICA algorithm performs the separation based upon an optimum weight matrix which has been calculated as a result of an evolutionary minimization algorithm over the HSIC measure. The optimum weight matrix is then applied to the input X in order to obtain the independent output signals ,namely the background and the foreground images which is interested. The complete algorithm is shown in Algorithm (1).

Algorithm 1. HSIC-PSO -ICA

Inputs: $X_F \in R^{n\times n}$ (F-GND); $X_{BF} \in R^{n\times n}$ (B+F-GND)

$X = [X_F; X_{BF}]_{2\times K}$

ICA Separation

Init. $W_{2\times 2}^{(t=0)}$ = random

$Y=[Y_F;Y_B]=WX$ (initial unmixing)

PSO-Optimization ()

Initialization: # init. population=50; # init. population=50
parameters =4; c1=c2=2

Loop

(Linear Kernel) $M_{k\times k} = X_F X_F^T$

(RBF Kernel) $K_{k\times k} = \exp(-\gamma\left\|X_{B_i} - X_{B_j}\right\|^2)$

$H_{ij} = \delta_{ij} - k^{-1}$ (Centering Matrix)

(Cost Function) $\text{HSIC}=(k-1)^{-2}\text{tr}\{\text{KHMH}\}$

$W_{opt.} = \text{argmin(HSIC)}$ (Optimized in PSO)

end loopPSO

$Y=[Y_F;Y_B]_{2\times k} = W_{opt.}X$

end ICA

F = Apply Morphological Operations (Erosion + Closing) onY_F

Output: **F**

4. 2. Morphological Operations Morphological operation works on the basis of set theory. The goal is to remove imperfections in the structure of an image.The basic operators are erosion, dilation, opening, and closing [24]. Here, we use a combination of two important operations, namely closing and erosion. The operations use a small matrix structure called structuring element. The shape and size of the structuring element has significant impact on the final outcome.

Erosion by small structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions.

The erosion of the image f by structuring element B at arbitrary location (x,y) is defined as:

$$f\Theta B(x,y)=\min_{(s,t)\in B}\{f(x+s,y+t)\} \quad (10)$$

Closing with small structuring elements fills holes in the regions while keeping the initial region sizes. Closing of the image f by structuring element B at arbitrary location (x,y) is defined as:

$$f \bullet B(x,y) = [(f \oplus B)\Theta B] \quad (11)$$

5. EXPERIMENTAL RESULTS

The dataset(Wallflower) consists of seven video sequences from the most important challenges including Bootstrapping(B), Camouflage(C), Foreground Aperture(F), Light Switch(LS), Moved Object(MO), Time of Day(TD) and Waving Trees(WT). A brief explanation of each challenge is mentioned in [25]. In each of the sequences, only one image contains the ground truth, and other frames are used either as a foreground or reference background.

In order to compare the performance of the foreground extraction algorithms, the segmented output is compared with the ground truth binary mask. To evaluate a segmented foreground, four values are computed from the prediction confusion matrix: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). These values are then used to compute three significant Measures: Recall, Precision and F-Measure [26]. These important evaluation metrics are defined with Equations (12)-(14):

$$\text{precision} = \frac{TP}{TP+FP} \quad (12)$$

$$\text{Recall} = \frac{TP}{TP+FP} \quad (13)$$

$$\text{F-Measure}=2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (14)$$

The sum of FP and FN denotes the error measure that is:

$$\text{Error} = FP+FN \quad (15)$$

The used hardware is a CPU-based core i7, with 8 GBytes of RAM, and Matlab R2019b is used as the platform to implement the codes.

These measures for different comparing algorithms are depicted in Figures 4-6. We need to mention that for the moving object sequence, the F-measure could not be shown for this dataset, due to the fact that its associated ground truth contains no foreground pixels. As it is shown, the proposed method outperforms the best methods over the FA(Foreground Aperture) sequence and performs almost equally with the best methods over the sequences of LS (Light Switching) , C (Camouflage) and WT(Waving Trees), namely MOG-MRF, GAC-ICA, and DCNN.

The total error over the entire sequences is shown in Figure 7, the proposed method is very competitive. Considering the fact that the proposed method contains minor post processing compared to the other methods the achieved error is remarkable.

The advantage of the proposed method over these methods is that the training period is much less, and the entire computation time is about 5 msec. Time coplexity is also obsserved during our evaluations.

Table1 compares the the performance of proposed Method over the wallflower dataset. As can be seen, the fastICA method has shorter training period, but the separation results are not satisfying. However, the HSIC-ICA has better outcome and similar training period.

The visual quality comparisons are presented in Figure 8, the proposed method has more plausible results and preserves the edges and fill holes, while other methods contain some artifacts or unsmooth results.

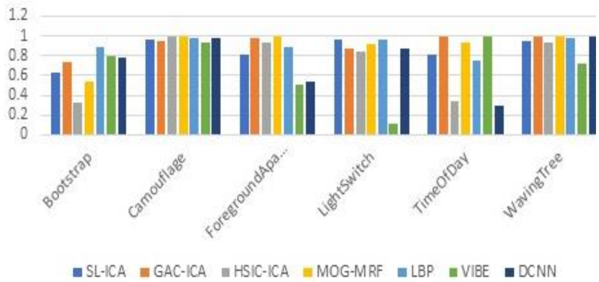

Figure 4. Precision on Wallflower dataset

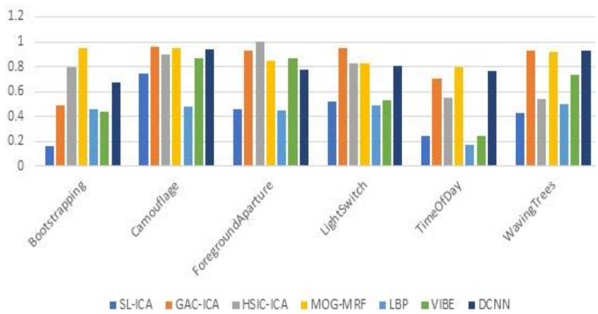

Figure 5. Recall on Wallflower dataset

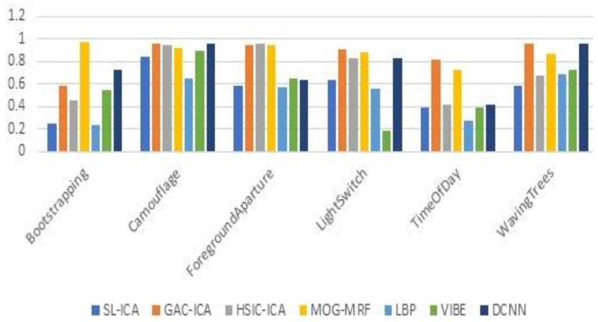

Figure 6. F-measure on Wallflower dataset

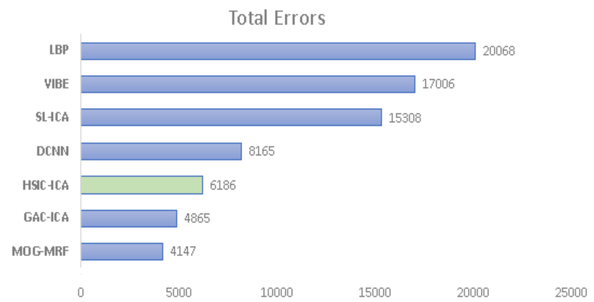

Figure 7. Total error comparison over the entire sequences of the WallFlower dataset.

TABLE 1. Train and test time complexity

Algorithms	Training (F/s)	Testing (F/s)
FastICA[11]	3.7	0.048
SL-ICA[11]	1.2×10^3 (150 iteration)	0.005
HSIC-ICA	**7 (150 iteration)**	**0.005**

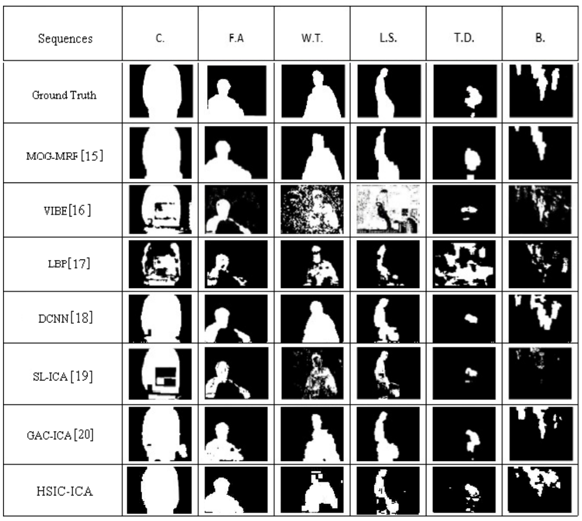

Figure 8. A comparison of the proposed method and other competitive methods of foreground extraction over the dataset

6. CONCLUSION

In this paper the problem of foreground extraction, in the presence of a reference background image, using a fixed camera is addressed. However, the background image might have been exposed to the illumination changes, light switching, and other challenging effects. Leveraging the prior that the foreground and background images are independent signals, the ICA algorithm has been employed, however with a different optimization cost function and searching algorithms. The cost function presented in this paper is called Hilbert-Schmidt Independence Criterion (HSIC), which can directly point toward the independence of the output signals (in contrast to the conventional ICA algorithms). Furthermore, the searching strategy is based on the particle swarmoptimization (PSO) evolutionary optimization method which is robust against being stuck in the local minima, and is also very fast. The experimental results over the Wallflower dataset, clearly shows the efficacy of our proposed method and its competing ability versus other methods. Many further post-processing tasks could be implemented to enhance the output of this method and could be among our future tasks.

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Persian Abstract

چکیده

استخراج پیش زمینه یکی از موضوعات مهم در پردازش تصویر است که کاربردهای مختلفی را در صنعت به دنبال دارد. علت استمرار تحقیق در این حوزه، چالش‌هایی است که در طی مراحل جداسازی تصاویر پیش زمینه و پس زمینه با آن‌ها روبرو می‌شویم. در میان روش‌های جداسازی منابع، روش تجزیه به مؤلفه‌های مستقل (ICA) رایج‌ترین است، که در حوزه‌های مختلف جداسازی سیگنال مورد استفاده قرار گرفته است. علیرغم پیشرفت‌هایی که در استخراج پیش زمینه حاصل شده، تغییرات روشنایی ناگهانی و حرکات پس زمینه بر نتایج این روش‌ها تأثیر منفی می‌گذارد. در این مقاله یک روش نوین به نام HSIC-ICA معرفی شده که چالش‌های مذکور را با استفاده از یک نسخه اصلاح شده از الگوریتم ICA برطرف می‌نماید، که به جای توابع هزینه متداول، از معیار استقلال هیلبرت–اشمیت (HSIC) استفاده می‌کند. علاوه بر این ماتریس جداکنندگی ICA از طریق الگوریتم تکاملی ازدحام ذرات (PSO) به طور سریع‌تری استخراج می‌شوند. نتایج آزمایش به وضوح نشان از برتری عملکرد ساختار پیشنهادی نسبت به سایر روش‌های پیشین روی مجموعه داده‌های Wallflower را نشان می‌دهد.